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STREAMFLOW FORECASTING USING ARIMA-BASED TIME SERIES MODEL - A CASE STUDY ON GORAI RIVER IN BANGLADESH

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ABSTRACT

Reliable streamflow forecasting is crucial for sustainable water resource management. In Bangladesh, strong seasonal variability makes the streamflow more challenging to forecast. This study applies univariate time series modelling strategy for streamflow forecasting in the Gorai river system. For that purpose, the historical streamflow data were collected for two hydrological stations: Gorai Railway Bridge (SW99) and Kamarkhali Transit (SW101) stations. These data were resampled at a consistent interval of 15 days. An extensive grid search method was applied to find the best model for both the stations. About 576 different models, including AR, MA, ARMA, ARIMA, and SARIMA, were tested for each station. Based on the Akaike Information Criterion (AIC), the SARIMA(1,1,1)(2,1,2,24) and the SARIMA(2,1,2)(1,1,2,24) were identified as the optimal models for the SW99 and SW101 stations, respectively. The optimal models were then applied to make one-step, two-step, and full multi-step forecasting. The performance of the model was evaluated using Nash-Sutcliffe efficiency (NSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). At Gorai Railway Bridge station, the model yielded NSE values of 0.814, 0.723, and 0.508, while at Kamarkhali Transit station, the model achieved 0.863, 0.787, and 0.672, in one-step, two-step, and multi-step, respectively.

Keywords: *Streamflow forecasting, ARIMA, Seasonality, SARIMA, Time series model.*

1. INTRODUCTION

Hydrological streamflow forecasting is critical for flood mitigation, effective water resource management, and reservoir operation planning (Awchi, 2014; Girihagama et al., 2022). However, reliable streamflow forecasting is always difficult due to the inherent complexity, non-linear, and non-stationary nature of the hydrological process (Yaseen et al., 2015; Zhang et al., 2021). Every river and its branches come with unique characteristics that influence the surrounding land and water systems (Zhang et al., 2021). In Bangladesh, streamflow exhibit highly seasonal variability (Rudra & Alam, 2023). During the monsoon season, rivers experience high flows that can lead to flooding. During the dry season, flows become stable and create water scarcity for agriculture and domestic use. This makes the streamflow forecasting more challenging in this region (Masood et al., 2015).

Traditional hydrological forecasting methods can be broadly categorized into two main approaches: process-driven models and data-driven empirical methods (Ding et al., 2020). Process-driven hydrological methods are physics-based models that can understand the rainfall-runoff relationship (Awchi, 2014). However, the physics-based models require extensive hydrological, hydrogeological and meteorological dat. In many regions of Bangladesh, such comprehensive datasets are not readily available (Masood et al., 2015). On the other hand, data-driven models offer an alternative approach. These models identify the direct statistical patterns in historical data without explicitly knowing the underlying physical process (Zhang et al., 2021). Among data-driven methods, time series modelling has proven highly effective for reliable hydrological forecasting (Karunasinghe & Liong, 2006; Azad et al., 2022a; Ratul et al., 2025). The Box-Jenkins family of models (Box et al., 1994), including Auto Regressive (AR), Moving Average (MA), and Auto Regressive Integrated Moving Average (ARIMA) models are widely used in hydrological applications (Adhikary et al., 2012; Banerjee et al., 2020; Selvaraj et al., 2020; Azad et al., 2022a, b). These models are particularly advantageous when historical streamflow records are available, but other related variables are limited or unreliable (Ghimire, 2017). However, hydrological time series data often contain seasonal variations that the standard ARIMA model may not adequately capture (Adhikary et al., 2018; Nguyen et al., 2025). In order to address the aforementioned limitations, the Seasonal ARIMA (SARIMA) model was introduced as an extension of the traditional ARIMA model (Wong et al., 2007). These models are specifically designed to capture seasonal behavior in hydrological data.

Bangladesh is one of the largest active deltas in the world; around 405 rivers flow in this country (BWDB, 2020). These rivers play a pivotal role to support the agriculture, ecology, and environment of this region. The Gorai River is one of the major rivers in the southwestern region of Bangladesh (Islam & Gnauck, 2011). During the dry season, when freshwater inflow becomes critical for local communities and ecological balance, the Gorai River becomes the essential source of freshwater (Rahman & Navera, 2018; Saim & Rahman, 2021). Despite its significance, previous hydrological research on the Gorai River has been limited. Previous studies have primarily focused on environmental flow assessment and sediment dynamics of the Gorai River (Ali & Hasan, 2022; Bomer et al., 2019). To date, no studies have been conducted to evaluate the streamflow forecasting in this river. This study addresses this gap by applying stochastic time series models to forecast streamflow of the Gorai River. We evaluate models, including AR, MA, ARMA, ARIMA, and SARIMA. These statistical models are particularly suitable for this study because, except streamflow data, other meteorological data are mostly limited for this region. It is expected that the outcome of this research will provide valuable insight into the predictability and hydrological behavior of the Gorai River and support operational water management decisions in the southwestern region of Bangladesh.

2. METHODOLOGY

2.1 The Study Area and Data Used

The Gorai River is the upper course of the Gorai-Madhumati-Baleswar River system and originates as a major distributary of the Ganges–Padma River near Kushtia District (Ali & Hasan, 2022). It is a critical hydrological lifeline for the southwest region of Bangladesh. The catchment area of the Gorai River is approximately 15160 sq. km (Islam & Gnauck, 2011). The annual hydrological discharge of the Gorai river shows a consistent seasonal pattern. During the monsoon period, from June to October, the river shows high streamflow with an average discharge of 2000 m3/sec. Followed by a dry season from November to May, with minimal precipitation, the river discharge becomes extremely low. In this study, two hydrological stations along the Gorai River were selected for analysis. The stations are Gorai Railway Bridge (Station ID: SW99) and Kamarkhali Transit (Station ID: SW101). The detailed characteristics of both hydrological stations are presented in Table 1. The Gorai Railway Bridge station is located in the upstream reach of the Gorai River, approximately 11.75 km downstream from the Ganges–Gorai bifurcation point (Figure 1). The Kamarkhali Transit Station is located approximately 76km downstream from the Gorai Railway Bridge Station.

Table 1: Description of selected hydrological monitoring stations.

Station Name	Station ID	River	District	Upazila	Latitude	Longitude
Gorai Railway Bridge	SW99	Gorai	Kushtia	Kamarkhali	23.8861°	89.1806°
Kamarkhali Transit	SW101	Gorai	Faridpur	Madhukhali	23.5391°	89.5169°

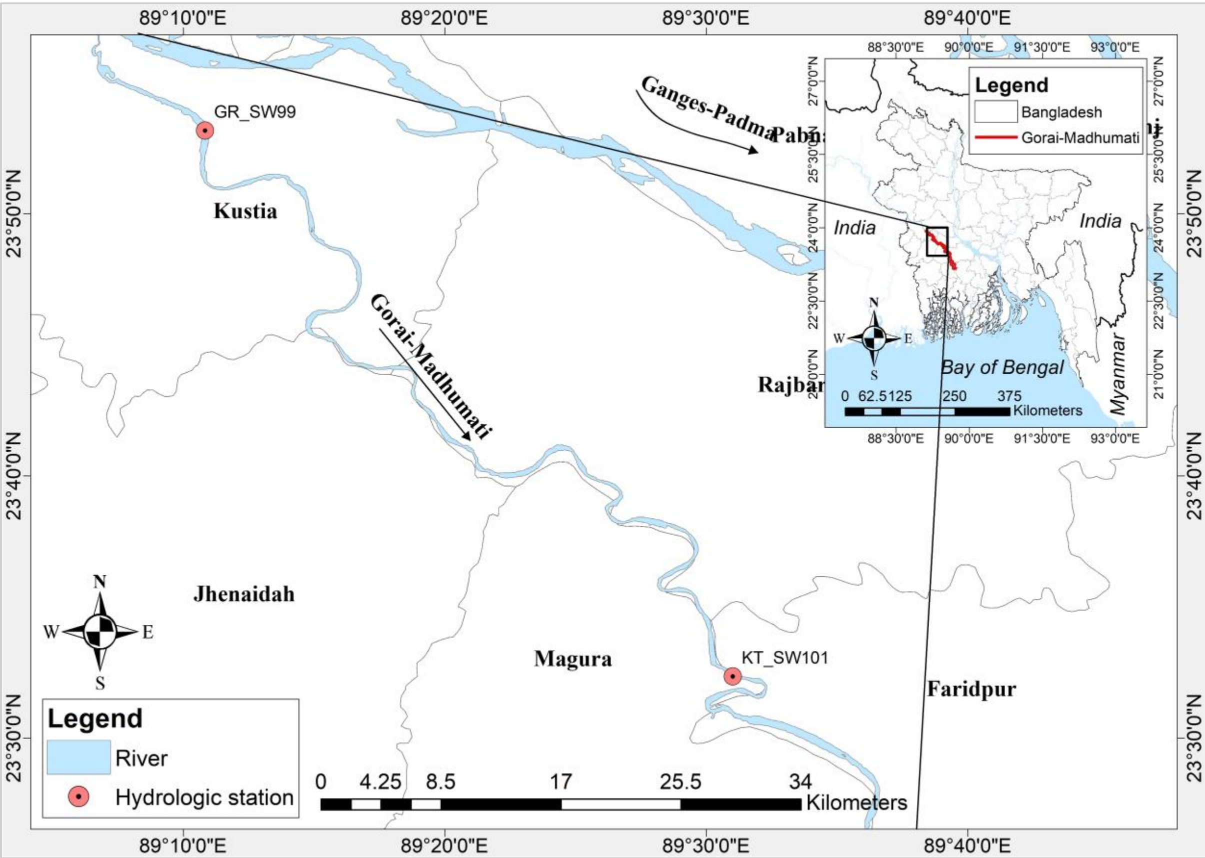

Figure 1: Location of the study area and hydrological stations along the Gorai River in Bangladesh.

2.2 Data collection and Preparation

In the current study, the streamflow data were collected from the Bangladesh Water Development Board (BWDB) from 1999 to 2019. The raw measured data were found at an irregular interval of 7 to 14days. Time series modeling techniques, such as ARIMA, require regular interval data for model building. For that reason, the collected data were needed to be pre-processed accordingly. First, an initial data screening was conducted to identify and remove the outliers from the raw measurement. The streamflow data were then resampled to a uniform 15-day interval, which corresponds to 24 observations per year.

After resampling, a small portion of missing data remained for both stations. These data were filled by using the linear interpolation method. After pre-processing of the data, the complete time series data for each station was partitioned into training and testing subsets using an 80:20 split ratio. During the data split, the chronological order of the time series was strictly preserved. The earlier observation (January 1999 to July 2015) was assigned to the training set, and the most recent portion (August 2015 to August 2019) was reserved for testing. The training set was used for model identification, parameter estimation, and diagnostic checking, while the testing set was kept aside, which was only used to evaluate the forecasting performance of the developed model.

2.3 Modeling Framework

ARIMA models are popular statistical techniques for time series forecasting. It is among the most widely used models in hydrological applications due to its univariate forecasting capability. The ARIMA framework is comprised of three fundamental components: autoregression (AR), differencing (I), and moving average (MA). The general form of an ARIMA (p, d, q) model can be represented by Eq. (1) as follows:

$$\phi_p(B)(1-B)^d\, y_t = \theta_q(B)\epsilon_t \tag{1}$$

Where, y_t is the observed time series at time *t*, B is the backshift operator (By_t=y_{t-1}), p is the order of the autoregression, d is the degree of differencing, q is the order of moving average, $\phi_p(B)$ is the autoregressive polynomial, $\theta_q(B)$is the moving average polynomial and ε_t represents the random error term. In a hydrological context, the AR component captures the memory effect in river discharge, where current flow conditions depend on antecedent flows. The MA components account for the random shocks that propagate through the system over multiple time steps.

Hydrological time series such as river discharge can be highly seasonal due to the periodic climatic process. In Bangladesh, the river discharge reaches its maximum during the monsoon due to the heavy rainfall in this region. During the dry season, the river flow becomes steady. This seasonal pattern can be observed in almost all the rivers in Bangladesh. To capture this seasonality, Seasonal ARIMA (SARIMA) could be effective. The SARIMA model is an extension of the basic ARIMA model. It incorporates the seasonal autoregressive and moving average terms. A SARIMA model is denoted as SARIMA(p,d,q)(P,D,Q,m) as given in Eq. (2), where the P, D, and Q stand for the seasonal AR order, seasonal differencing order, and seasonal MA order, respectively.

$$\phi_p(B)\Phi_P(B^m)(1-B)^d(1-B^m)^D\, y_t = \theta_q(B)\Theta_Q(B^m)\epsilon_t \tag{2}$$

Where $\Phi_P(B^m)$ and $\Theta_Q(B^m)$ are seasonal autoregressive and moving average polynomials, respectively. In this study, the stream flow data for both the station were in 15-day intervals, hence the seasonal period m was 24 to the annual cycle.

2.4 Box-Jenkins Methodology

According to Box et al. (1994), ARIMA model building should follow four major steps: (i) model identification, (ii) parameter estimation, (iii) diagnostic checking, and (iv) forecasting, which was followed for model development and evaluation in the current study.

2.4.1 Model identification

Traditionally, model identification begins with ensuring stationarity in time series and then analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify the appropriate model order. However, in this study, we used an exhaustive grid search approach to find the candidate model's structure. This search strategy ensures comprehensive exploration of the model space and minimizes the risk of overlooking potentially superior model structures.

In order to find the parameter range in the search space, a preliminary ACF and PACF analysis was conducted on the training data under three configurations: (d, D) = (0, 0), (0, 1), and (1, 1), where d and D represent non-seasonal and seasonal differencing orders, respectively. For both hydrological stations, the ACF plot on the raw series (d, D = 0, 0) exhibited a clear seasonality at 24 lags (Figure 2a, 2d). Therefore, the first seasonal differencing (d =0, D=1) at 24 lag was necessary to remove the seasonality from the data. Although the seasonal pattern was largely eliminated, the ACF plot still showed a slow decay of significant spike in the nonseasonal space (Figure 2b, 2e). This suggests that the series has a trend of long-term dependence. Hence, a non-seasonal differencing (d = 1) was applied in the final configuration. For (d, D) = (1, 1), both the ACF and PACF plots tailed off quickly and showed no significant spike after 2 to 3 lags (Figure 2c, 2f). Based on this information, the search space was defined as follows:

$$p, q \in \{0,1,2,3\}; \; d, D \in \{0,1\}; \; P, Q \in \{0,1,2\}, and \; m = 24$$

This grid encompasses 4 × 2 × 4 × 3 × 2 × 3 × 1 = 576 unique model configurations, including pure AR, pure MA, ARMA, ARIMA, and SARIMA structures. Each configuration of model was fitted to the training dataset and the grid search was executed independently for both monitoring stations to find the best models.

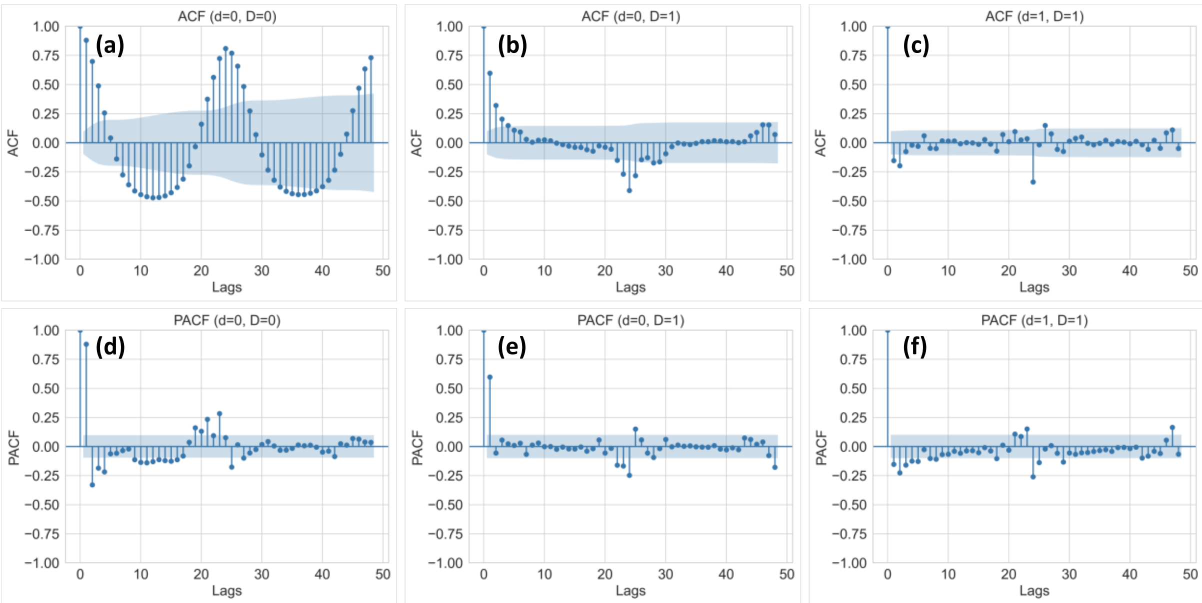

Figure 2: ACF (a–c) and PACF (d–f) plots for the SW99 hydrological station under three differencing configurations: (a, d) d = 0, D = 0; (b, e) d = 0, D = 1; (c, f) d = 1, D = 1.

2.4.1.1 Model Selection Criteria

To identify the optimal model, the Akaike information Criterion (AIC) was employed (Akaike, 1974). AIC estimates a model's ability to predict future observations based on its fit to the sample data. It balances model accuracy and complexity by penalizing excessive parameters. Lower AIC values indicate superior model performance. The AIC is defined by Eq. (3) as follows:

$$AIC = -2log(L) + 2k \tag{3}$$

Where, L is the maximum likelihood function and k is the number of estimated parameters. For each candidate model, the AIC value and the corresponding computational training time were computed. The model achieving the minimum AIC was selected as the optimal specification.

2.4.2 Parameter Estimation

Once the optimal model structure was identified through grid search, model parameters were estimated using maximum likelihood estimation (MLE). The MLE approach identifies parameter values that maximize the probability of observing the training data given the model structure.

2.4.3 Diagnostic Checking

Following parameter estimation, comprehensive residual diagnostics were conducted to verify model adequacy and validate underlying assumptions. The diagnostic procedures included residual distribution analysis, autocorrelation analysis, and normality assessment. Residual histograms were inspected to verify normality, zero mean, and constant variance. The residual ACF and PACF were examined to confirm the absence of temporal dependence among the residuals. Finally, the Ljung–Box test was applied to statistically assess remaining autocorrelation. The models whose residuals behaved as white noise were accepted for further forecasting.

2.4.4 Generation of Streamflow Forecasting

Once the optimal model was identified for both hydrological stations, three distinct forecasting strategies were implemented to evaluate model performance in different lead times. These strategies are: (i) one-step ahead (15-day), (ii) two-step ahead (30-day), and (iii) recursive multi-step ahead forecasting. The one-step (15-day) ahead approach produced forecasts for t+1 using all observed data up to time t. The two-step (30-day) ahead strategy extended the horizon to t+2, where only the second-step forecasts were stored and evaluated. These two strategies represent the model performance in short to mid-term forecasting. Finally, a recursive multi-step approach was employed to simulate long-range forecasting by sequentially predicting the entire test period, where each forecast was fed back into the model as new observations. Together, these three strategies simulate the real-world water resource management applications where lead time forecasts are required for decision-making.

2.5 Model Performance Evaluation

The model performance in the test set was evaluated using three statistical metrics, including Nash-Sutcliffe efficiency (NSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), which are given by Eqs. (4)-(6).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

Where, $\bar{y}$ is the mean of the observed values, y_i and $\hat{y}_i$ are the observed and predicted discharge values in time i, and N is the total number of observations. An NSE value of 1 indicates the model has perfectly forecasted the future data, an NSE value of 0 indicates the model performed equal to the mean of the observed data, and an NSE smaller than 0 indicates the model forecast is worse than the mean observation. A lower RMSE and MAE value indicates the model error is lower.

2.6 Software and System Used

In this study, all experiments were conducted on a system equipped with an AMD Ryzen 5 series processor and 4 GB of graphics processing unit (GPU). All the modelling process was performed in Python 3.12.7 using the JupyterLab environment. The ARIMA models were developed with the

Statsmodels library. Other necessary libraries were pandas and NumPy for data analysis and Matplotlib for the visualization task.

3. RESULTS AND DISCUSSION

3.1 Model selection and Evaluation

In this study, a comprehensive grid search procedure was used to evaluate 576 candidate models. These models covered AR, MA, ARMA, ARIMA, and SARIMA structures. For every candidate model, the AIC and training time were stored. The complete grid search required 1 hour 20 minutes for the Gorai Railway Bridge station and 1 hour 18 minutes for the Kamarkhali Transit station. Figure 2 shows the candidate models' performance results for both stations. Among all the combinations of models evaluated in the grid search, the SARIMA model showed the best performance in both hydrological stations.

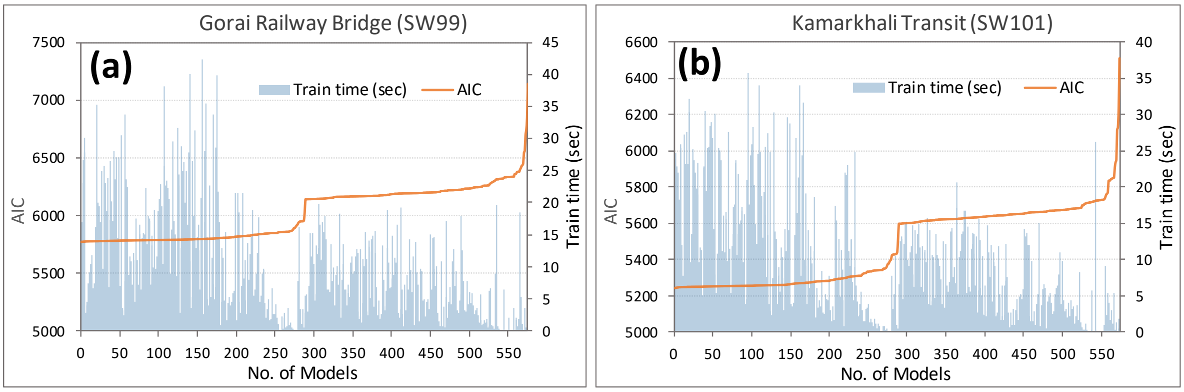

Figure 2: Distribution of AIC values across all candidate model with training time for (a) Gorai Railway Bridge (SW99) station, and (b) Kamarkhali Transit (SW101) station.

Table 2: Summary of the best performed SARIMA model based on the AIC value.

Station Name	Model No.	Order (p,d,q)	Seasonal Order (P,D,Q,24)	AIC	Train Time (sec)
Gorai Railway Bridge	1	(1,1,1)	(2,1,2,24)	5771.47	16.88
	2	(2,1,1)	(2,1,2,24)	5771.81	22.98
	3	(1,1,2)	(2,1,2,24)	5772.52	26.77
	4	(3,1,1)	(2,1,2,24)	5773.12	27.81
	5	(1,1,3)	(2,1,2,24)	5773.33	30.1
Kamarkhali Transit	1	(2,1,2)	(1,1,2,24)	5243.53	23.83
	2	(2,1,2)	(2,1,2,24)	5244.76	24.73
	3	(1,0,3)	(1,1,2,24)	5245.58	22.78
	4	(0,0,3)	(1,1,2,24)	5246.23	21.02
	5	(2,1,2)	(0,1,1,24)	5246.8	8.8

From Figure 2, it can be seen that the first 200 to 250 candidate models exhibited a very minimal AIC difference. This indicates that there were multiple near-optimal structures present for each hydrological station. The best model was selected based on the AIC criterion. Hence, the model with the lowest AIC value was selected for further analysis. Based on the AIC values, the top-performing models at each station are summarized in Table 1. At the Gorai Railway Bridge station, the SARIMA(1,1,1)(2,1,2,24) model had achieved the lowest AIC of 5771.47. At the downstream Kamarkhali Station, the optimal model was SARIMA(2,1,2)(1,1,2,24). This model achieved an AIC of 5243.53. Hence, these two models were selected for further diagnostic analysis.

3.2 Model Adequacy Assessment

In the diagnostic analysis, residual properties were examined to verify that the fitted SARIMA models satisfied the underlying assumptions. Figure 3(a) and 3(d) show the residual histogram for both hydrological stations. From the residual histograms, it was found that the residual distributions closely approximated a normal distribution with zero mean and constant variance. Figure 3(b) to 3(f) show the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the residuals for both stations. The ACF and PACF plot showed no significant spike at any lag. This indicated that, for both SARIMA(1,1,1)(2,1,2,24) and SARIMA(2,1,2)(1,1,2,24) models, the residuals were not significantly correlated at any lags.

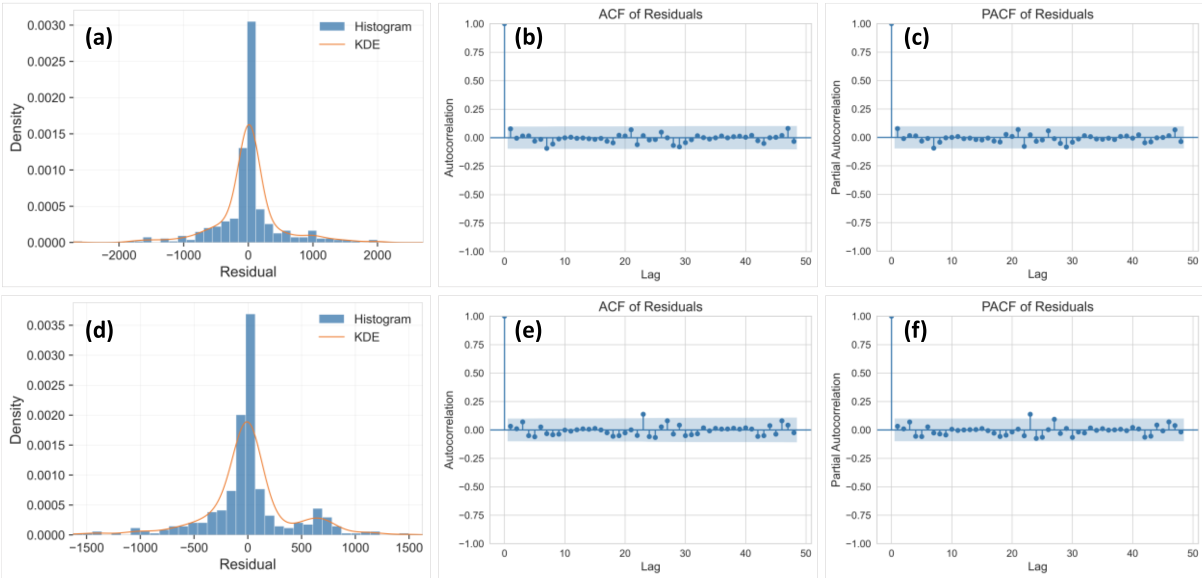

Figure 3: (a) Histogram and KDE of residuals, (b) ACF of residuals, (c) PACF of residuals for the Gorai Railway Bridge station, (d) Histogram and KDE of residuals, (e) ACF of residuals, (f) PACF of residuals for the Kamarkhali Transit station.

In order to further verify residual independence, the Ljung-Box test was conducted for lag 2 up to lag 72. Table 1 shows the Ljung-Box test results for both stations. The results show that the *p*-value consistently remained greater than the significance level for all the lags. This indicates that the null hypothesis of white noise could not be rejected. Collectively, these diagnostic results confirm that the residuals were uncorrelated and near-normally distributed. This validates the statistical adequacy of the fitted SARIMA models for reliable forecasting.

Table 3: Ljung-Box test Results.

Station	Model Structure	Lag Range	*p*-value	Significance	Interpretation
Gorai Railway Bridge	SARIMA (1,1,1)(2,1,2,24)	2–72	0.30-0.99	All $p > 0.05$	Residuals are white noise
Kamarkhali Transit	SARIMA (2,1,2)(1,1,2,24)	2–72	0.39–0.89	All $p > 0.05$	Residuals are white noise

3.3 Evaluation of Forecasting Performance

The optimal Seasonal ARIMA (SARIMA) models were applied to the test dataset (August 2015 to August 2019) to assess the models' forecasting performance on unseen data. Three forecasting strategies, one-step ahead (15-day), two-step ahead (30-day), and recursive multi-step ahead forecasting, were evaluated to represent the model's short to long-term forecasting performance. Table 4 presents the comparative performance results for both stations. The results indicate that the SARIMA model provided good performance in short-term forecasting. At the Gorai Railway Bridge station, the SARIMA(1,1,1)(2,1,2,24) model achieved NSE value of 0.81, RMSE of 502.47 m^3/s and MAE of 248.55 m^3/s in 15 days ahead forecast. For, 2 step (30 days) ahead forecast, the model achieved NSE value of 0.72, RMSE of 602.11 m^3/s and MAE of 325.76 m^3/s. The recursive multi-step streamflow forecasting strategy, the test NSE value dropped to 0.51, while RMSE and MAE escalated to 816.55 m^3/s and 467.93 m^3/s, respectively. The results obtained for the Kamarkhali Transit station demonstrated the superior forecasting performance than the Gorai Railway bridge station. For a one-step (15-day) ahead forecast, the SARIMA(2,1,2)(1,1,2,24) model achieved an impressive test NSE value of 0.86, slightly exceeding the training performance. Two-step-ahead forecasting maintained strong performance with NSE of 0.79, RMSE of 444.12 m^3/s, and MAE of 245.11 m^3/s. In the recursive multi-step streamflow forecasting, the model achieved NSE of 0.67, RMSE of 548.92 m^3/s, and MAE of 326.63 m^3/s.

Table 4: Summary of the forecasting performance of SARIMA models.

Station	**Model Structure**	**Forecast Type**	**Lead Time**	**NSE (Train)**	**NSE (Test)**	**RMSE (Test)**	**MAE (Test)**
Gorai Railway Bridge	SARIMA (1,1,1)(2,1,2,24)	1-step	15 days	0.85	**0.81**	**502.47**	248.55
		2-step	30 days	0.85	0.72	602.11	325.76
		Recursive multi-step	-	0.85	0.51	816.55	467.93
Kamarkhali Transit	SARIMA (2,1,2)(1,1,2,24)	1-step	15 days	0.85	**0.86**	**354.41**	193.14
		2-step	30 days	0.85	0.79	444.12	245.11
		Recursive multi-step	-	0.85	0.67	548.92	326.63

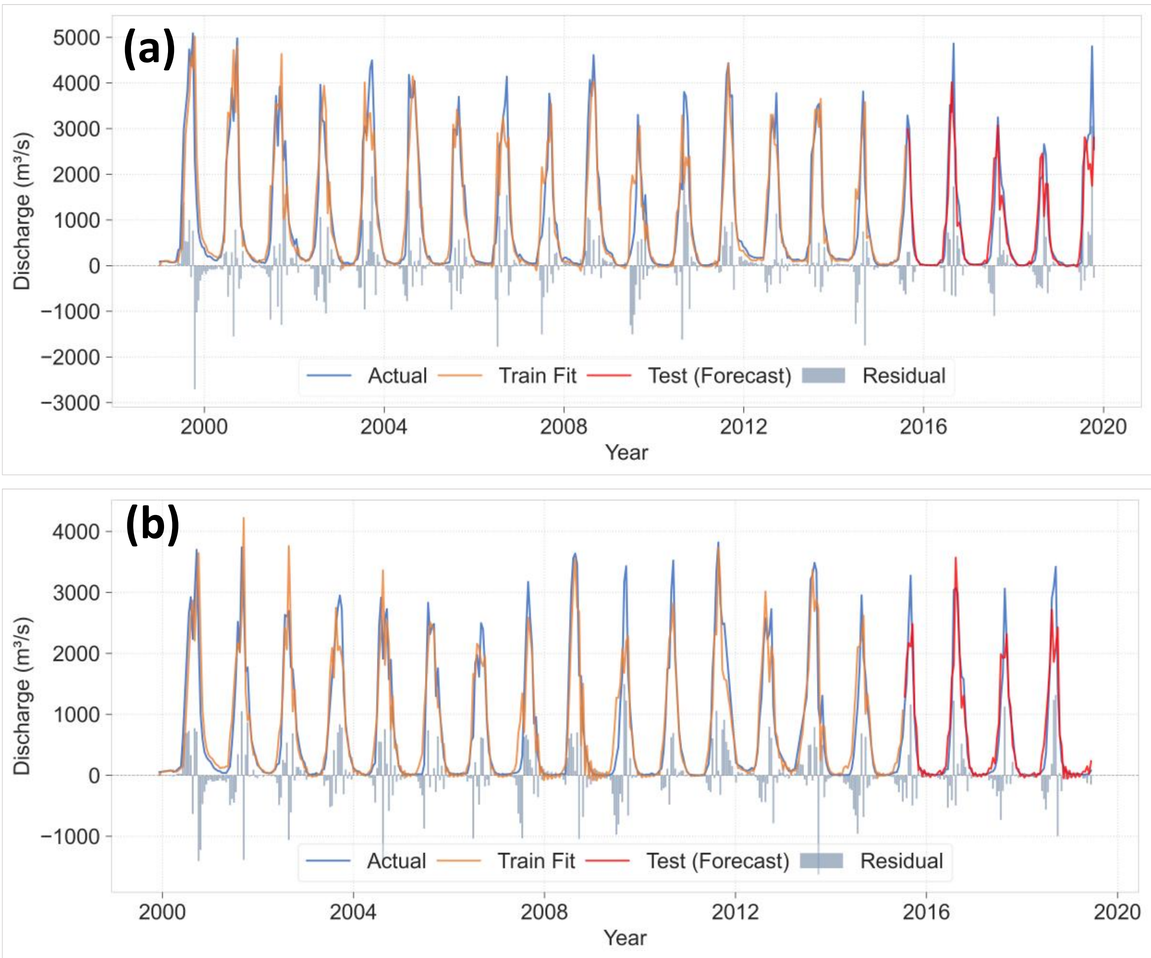

Figure 4: Actual and 1-step (15-day) ahead forecasted streamflow time series for (a) the Gorai Railway Bridge station, and (b) the Kamarkhali Transit station by the SARIMA model.

In order to further evaluate the model performance, the actual and forecasted data were evaluated in the time-series. Figure 4 represents the 1-step ahead forecast against the actual streamflow. From the plot, it can be seen that the SARIMA-based time series models had successfully captured the seasonal pattern of the Gorai River. For 1 step ahead forecasting, the models could accurately predict the timing and magnitude of peak discharge in the training and testing periods.

Figure 5 presents the recursive multi-step forecasting time series plot with the 95% confidence interval. Like the 1-step ahead forecasting, the recursive forecasting also captured the seasonal pattern in the test set. However, the model predictions were more monotonic and failed to capture the overshooting observations. In addition, with the extended forecast horizon, the model forecasted peaks started to occur one to two timesteps (e.g., about 15 – 30 days) earlier than the actual streamflow peaks. This behavior stems from the recursive forecasting mechanism, where each prediction is fed back as input for the next step. This creates cumulative errors that propagate forward. As a result, extreme values and sudden variations are gradually smoothed out, leading to more conservative predictions. For both the hydrological stations, the 95% confidence interval was found progressively widened as the forecast extended further from the training data. Notably, all the forecasted values remained within the error band. The streamflow forecasting results demonstrate that the developed SARIMA-based time series models are well-suited for short- to medium-term operational planning in the Gorai River. The high NSE values (0.72–0.86) for 15-day to 30-day forecasts support applications such as irrigation scheduling, navigation planning, and early warning systems in this river system.

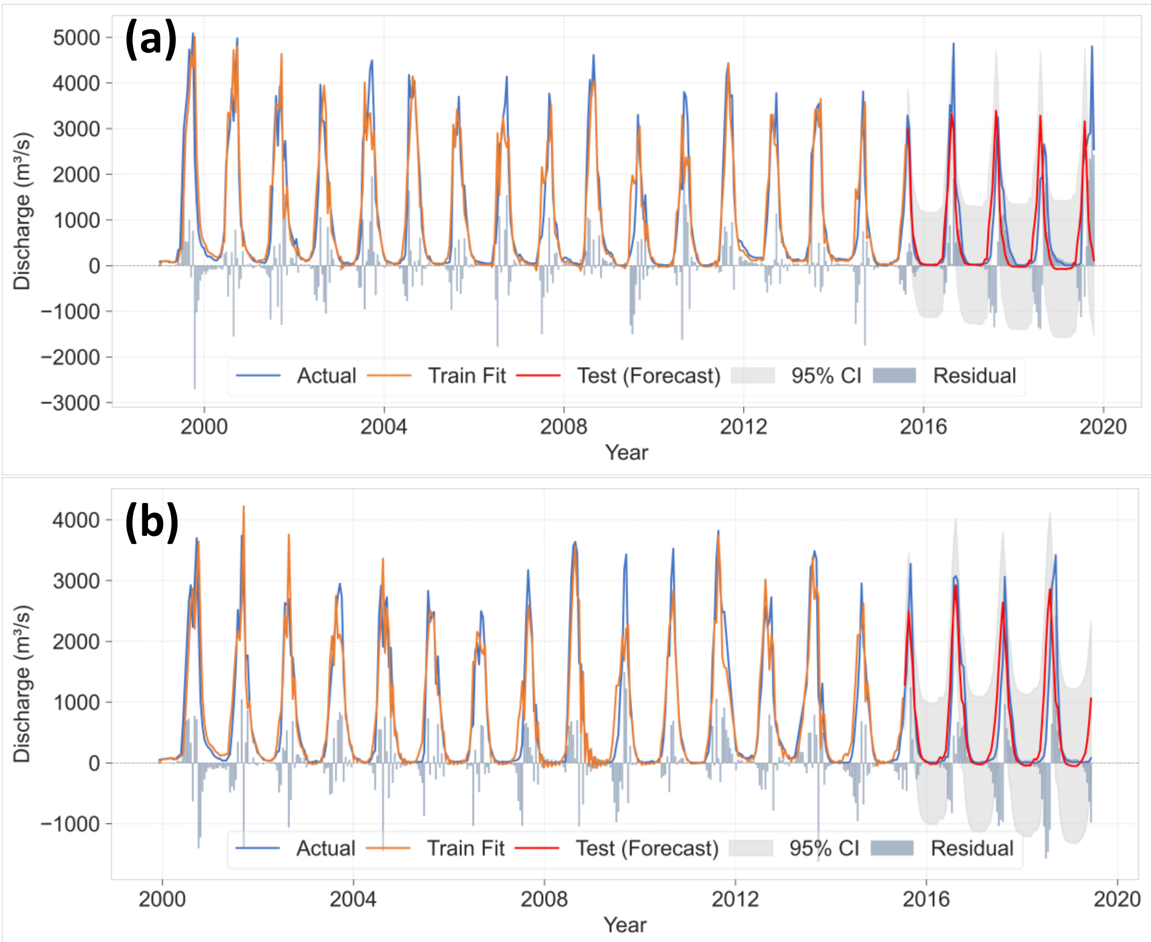

Figure 5: Actual and recursive forecasted streamflow time series for (a) the Gorai Railway Bridge station, and (b) the Kamarkhali Transit station by the SARIMA model with 95% confidence interval.

4. CONCLUSIONS

In the current study, the univariate time-series models were developed and evaluated for streamflow forecasting in the Gorai River of Bangladesh. For that reason, about 20 years of streamflow data were collected and used from two hydrological stations, namely Gorai Railway Bridge and Kamarkhali transit stations of the river. About 576 candidate models, including AR, MA, ARMA, ARIMA, and SARIMA, were evaluated by a grid search approach. Based on the Akaike Information Criterion (AIC), the SARIMA(1,1,1)(2,1,2,24) and SARIMA(2,1,2)(1,1,2,24) models were identified as optimal for the Gorai Railway Bridge (SW99) and Kamarkhali Transit (SW101) stations, respectively. Both models achieved strong short-term forecasting accuracy. For the 15-day ahead forecast, the models achieved NSE values of 0.81 and 0.86 at the SW99 and SW101 hydrological stations, respectively. For the 30-day ahead forecast, the forecasting performance of the models remained acceptable with NSE of 0.72 and 0.79, respectively. However, in the long-term streamflow forecast, the SARIMA model's performance declined. In a multi-step recursive forecast, the SARIMA model achieved an NSE value of 0.51 to 0.67 for the Gorai Railway Bridge station and the Kamarkhali transit station, respectively. In every forecasting strategy, the SARIMA-based time series model exhibited the superior performance in the Kamarkhali Transit station than that of the Goria Railway Bridge station. From an operational point of view, the developed models can be used for short to mid-term (about 15 – 30 days) irrigation scheduling, navigation planning, and early warning systems for the Gorai River. However, we strongly suggest that these models should be applied cautiously for the long-term planning (e.g., annual scale) and management purposes.

DECLARATION OF USE OF AI

We declare that AI was only used as a writing tool to refine the language and grammar in this paper. It ensured that all methodological framework, analysis and modeling tasks of the current work were independently developed by the authors.

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